

1 **Assessing Bayesian Phylogenetic Information Content of Morphological Data Using**
2 **Knowledge from Anatomy Ontologies**

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28 **Abstract.** Morphology remains a primary source of phylogenetic information for many
29 groups of organisms, and the only one for most fossil taxa. Organismal anatomy is not a
30 collection of randomly assembled and independent ‘parts’, but instead a set of dependent and
31 hierarchically nested entities resulting from ontogeny and phylogeny. How do we make sense
32 of these dependent and at times redundant characters? One promising approach is using
33 ontologies—structured controlled vocabularies that summarize knowledge about different
34 properties of anatomical entities, including developmental and structural dependencies. Here
35 we assess whether the proximity of ontology-annotated characters within an ontology predicts
36 evolutionary patterns. To do so, we measure phylogenetic information across characters and
37 evaluate if it is hierarchically structured by ontological knowledge—in much the same way as
38 phylogeny structures across-species diversity. We implement an approach to evaluate the
39 Bayesian phylogenetic information (BPI) content and phylogenetic dissonance among
40 ontology-annotated anatomical data subsets. We applied this to datasets representing two
41 disparate animal groups: bees (Hexapoda: Hymenoptera: Apoidea, 209 chars) and
42 characiform fishes (Actinopterygii: Ostariophysi: Characiformes, 463 chars). For bees, we
43 find that BPI is not substantially structured by anatomy since dissonance is often high among
44 morphologically related anatomical entities. For fishes, we find substantial information for
45 two clusters of anatomical entities instantiating concepts from the jaws and branchial arch
46 bones, but among-subset information decreases and dissonance increases substantially
47 moving to higher level subsets in the ontology. We further applied our approach to address
48 particular evolutionary hypotheses with an example of morphological evolution in miniature
49 fishes. While we show that ontology does indeed structure phylogenetic information,
50 additional relationships and processes, such as convergence, likely play a substantial role in

51 explaining BPI and dissonance, and merit future investigation. Our work demonstrates how
52 complex morphological datasets can be interrogated with ontologies by allowing one to
53 access how information is spread hierarchically across anatomical concepts, how congruent
54 this information is, and what sorts of processes may structure it: phylogeny, development, or
55 convergence.

56

57 **Keywords:** Apidae, Bayesian phylogenetic information, Ostariophysi, Phenoscape,
58 phylogenetic dissonance, semantic similarity.

59

60 **Running heads:** PHYLOGENETIC INFORMATION IN ANATOMY ONTOLOGIES

61

62 Phylogeny is the key to making sense of biodiversity. It structures the vast variation of form
63 among species into an understandable map that we can use to place and organize all life,
64 compare and contrast organisms, and recover the individual and shared evolutionary history
65 for each lineage and group. By structuring knowledge about data in meaningful ways, a
66 phylogeny allows us to extract information from biological data and ultimately, biological
67 meaning, in ways that would be impossible without it. The hierarchical nature of life,
68 however, is evident not just at the level of species (e.g., Oakley 2003; Serb and Oakley 2005).
69 It is also observed among phenotypic traits, which are themselves often descended from
70 common ancestral precursors modified over developmental and evolutionary time frames.
71 Therefore, organismal anatomy is not a collection of randomly assembled ‘parts’. It is the
72 manifestation of relationships among anatomical entities and structure resulting from
73 ontogeny and phylogeny. Just as we can organize knowledge about species with phylogeny,
74 our definitions of the entities, qualities, and relations of organismal traits can be organized by
75 ontologies—structured controlled vocabularies formalizing relationships among concepts
76 (Mabee et al. 2007; Vogt 2009; Deans et al. 2015).

77 Ontologies summarize knowledge about different properties of anatomical entities,
78 including developmental and structural dependencies. For example, in fishes, the presence of
79 a ‘dorsal fin ray’ is dependent on the presence of a ‘dorsal fin’. Here, we explore one
80 particular aspect from ontologies: do ontology concepts referring to real anatomical entities
81 and the relations among them structure phylogenetic information? In other words, does the
82 proximity of characters within an ontology with respect to their anatomical and structural
83 relations predict their evolutionary patterns? Investigating this question is key to
84 understanding the processes underlying morphological evolution and to addressing key
85 impediments to the ‘Phenomics’ revolution (Deans et al. 2015)—namely, the complex sets of

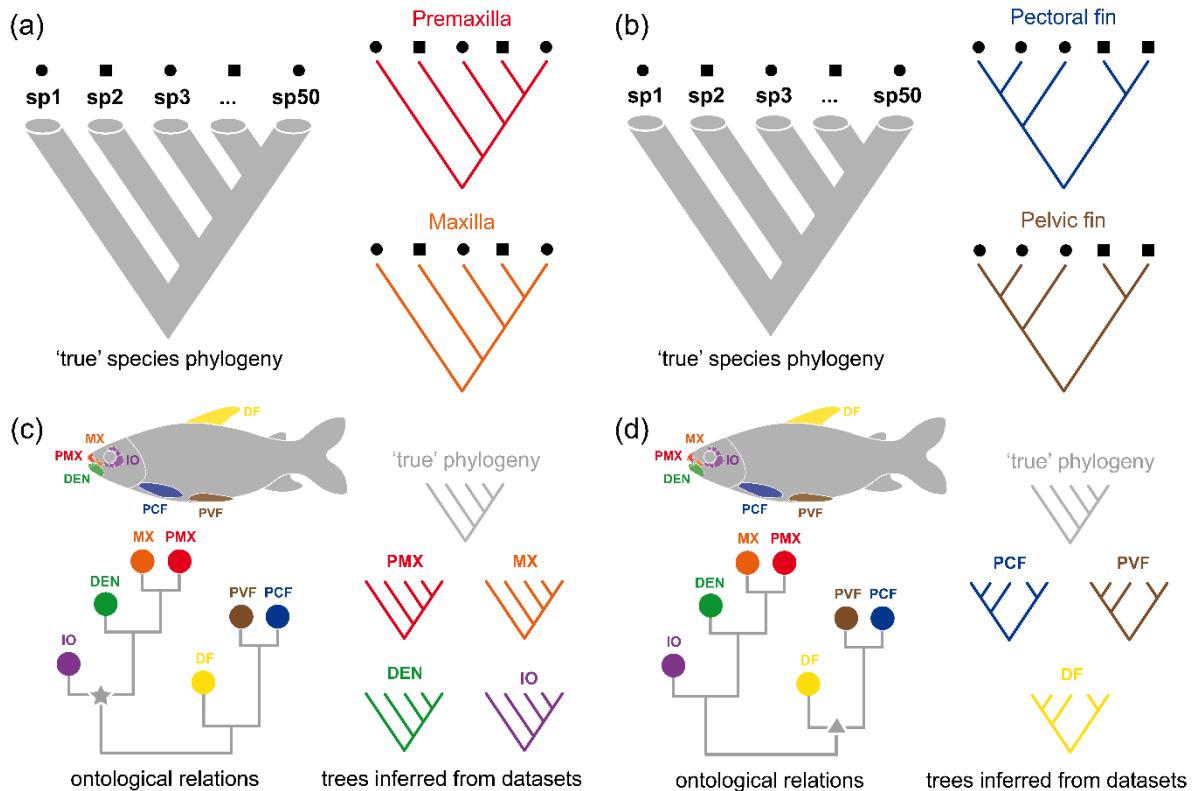
86 dependencies among phenotypic characters that confound the application of traditional
87 statistical models.

88 In contrast to molecular data, which are typically treated as independently-evolving
89 sets of characters, morphological data are known to carry dependencies and redundancies
90 across characters. Morphological traits may change in a concerted fashion through
91 evolutionary time (i.e., evolutionary modules) if they share a common underlying
92 genetic/developmental machinery (Lewontin 1978; Wagner 1989, 1996, 2007; Wagner and
93 Altenberg 1996; Wagner and Stadler 2003; Mabee 2006) and/or as a result of shared
94 functional/ecological selective pressures (e.g., see concerted convergence: Patterson and
95 Givnish 2002; Holland et al. 2010; Blank et al. 2013). Therefore, groups of characters may
96 imply similar trees due to shared phylogenetic history (Fig. 1a) or convergence (Fig. 1b), and
97 in both cases may over-represent the degree of support if treated as independent realizations
98 of a stochastic evolutionary process. In this context, ontology knowledge may provide us with
99 additional insights (e.g., from anatomy and development) into the historical patterns of trait
100 changes: Do particular classes of anatomical entities provide more phylogenetic information
101 than others (Fig. 1c)? How semantically diverse are the anatomical concepts that support a
102 particular topology? Is there conflict between different sets of anatomical concepts that may
103 suggest convergence or other evolutionary processes (Fig. 1d)?

104 Here, we develop a view that is distinct from typical partitioning of phylogenetic
105 datasets. Approaches to assess and/or account for heterogeneity across subsets/partitions of
106 molecular data (e.g., genes, codon positions) usually focus on rates and/or model of trait
107 evolution (see review in Kainer and Lanfear 2015); informativeness (e.g., Townsend 2007;
108 Townsend et al. 2012); or topological conflict among inferred trees (e.g., Zhou et al. 2020;
109 Smith et al. 2020). However, much like how partitioning taxa into a flat set of genera or
110 families is inadequate to represent phylogenetic structure, partitions in the traditional sense

111 fail to account for the continuous hierarchical relations among characters. Expanding
112 partitions among characters into hierarchical structures enables new questions to be asked of
113 phylogenetic data.

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117 **FIGURE 1.** Comparison of the 'true' species phylogeny with trees inferred from different data
118 subsets. (a) Trees inferred from characters of 'premaxilla' and 'maxilla' are congruent and
119 indicate true phylogenetic information. (b) Trees inferred from characters of 'pectoral fin' and
120 'pelvic fin' are congruent between themselves but not with the 'true' species phylogeny, thus
121 indicating convergence, in this case, associated with other ecological/functional factors
122 (squares and circles). (c) Ontology relations among anatomy entity concepts showing that
123 related anatomical entities (for example, the node indicated with a star) provide true
124 phylogenetic information. (d) Ontology relations among anatomy entity concepts showing that
125 related anatomical entities (for example, the node indicated with a triangle) provide no
126 phylogenetic information, but are jointly influenced by convergent evolution. Abbreviations:
127 DF, dorsal fin; DEN, dentary; IO, infraorbital; MX, maxilla; PCF, pectoral fin; PMX,
128 premaxilla; PVF, pelvic fin; sp1...sp50, species in a dataset. For colors, please refer to the
129 online version of this paper available at [XXX](#).
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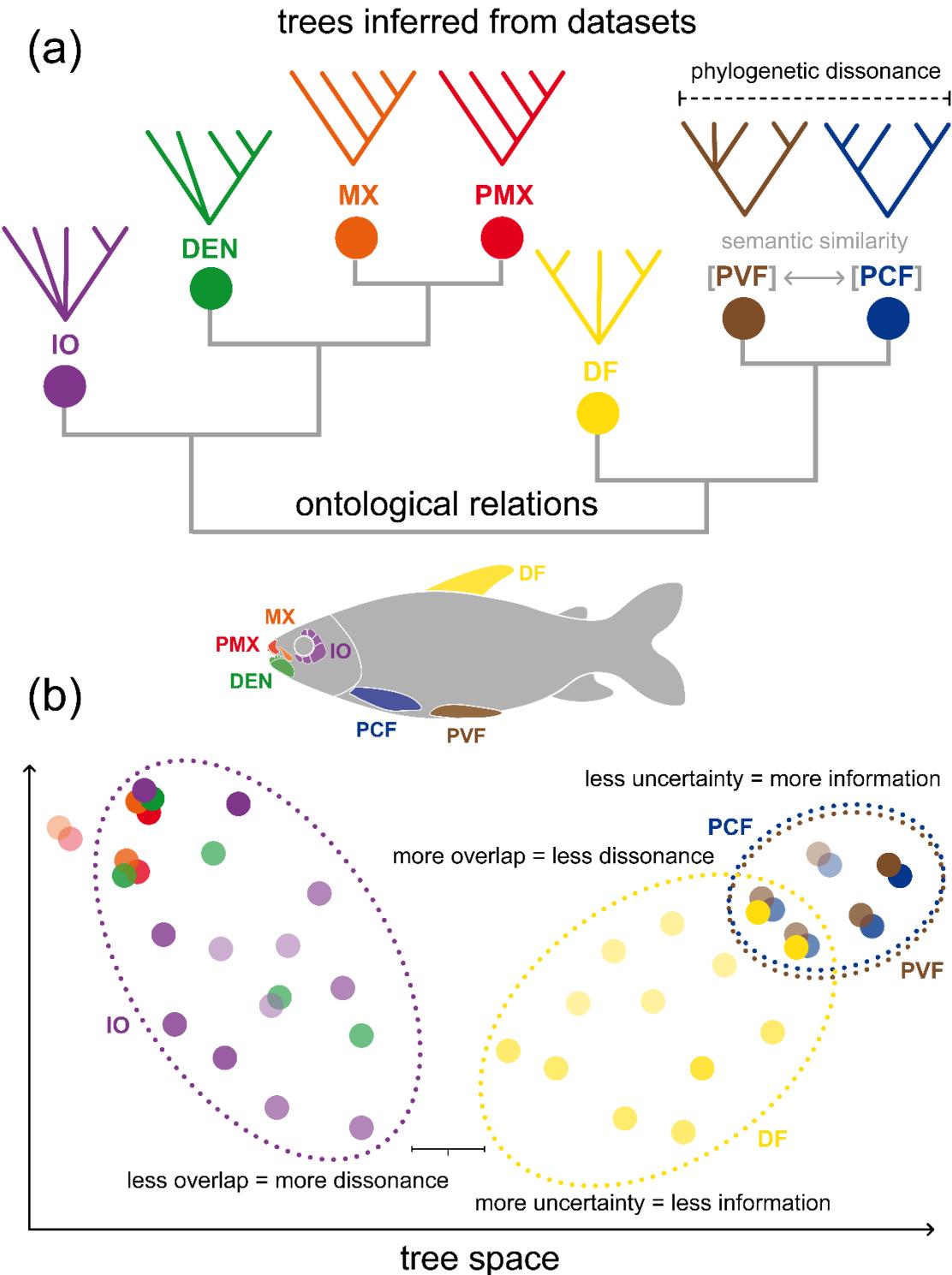
131 One such fundamental question is to ask how information about the phylogeny is
132 structured across characters. Here, we address this question by integrating knowledge from
133 ontologies with the Bayesian phylogenetic information (BPI) framework proposed by Lewis
134 et al. (2016) (see also Neupane et al. 2019; Porto et al. 2021). Lewis' et al. framework is
135 based on Shannon's (1948) entropy and Lindley's (1956) information. In short, Shannon's
136 entropy measures uncertainty in discrete outcomes and Lindley's information measures how
137 data make some outcomes more probable than others. In Lewis' et al. context, the outcomes
138 refer to discrete tree topologies in the posterior distribution. Therefore, (Bayesian)
139 phylogenetic information is used here in a sense that differs from most common usages.
140 Phylogenetic information usually refers to the information inferred from data about the 'true'
141 evolutionary history of organisms (see discussion on phylogenetic systems in Farris 1979). A
142 related concept is phylogenetic signal, which refers to similarity among an organismal trait (or
143 set of traits) in different taxa that is explained by shared evolutionary history (Pagel 1999).
144 BPI here refers to the 'ability' of data to concentrate prior probabilities of tree topologies into
145 a smaller set of trees in the posterior (as in Lewis et al. 2016).

146 Lewis's et al. approach allows us to assess information inferred from data, but also to
147 evaluate how different data subsets may concentrate probabilities into alternative sets of trees
148 through a measure called phylogenetic dissonance (Lewis et al. 2016). Data subsets may
149 represent groups of characters from different anatomical regions. They can be compared to
150 evaluate which ones are congruent with each other and/or with the 'true' phylogeny, for
151 example. Ontology knowledge can be integrated by structuring such comparisons in a
152 meaningful way based on known relations (e.g., anatomical/developmental) among anatomy
153 entity concepts instantiated by characters annotated in these data subsets (Fig. 2a). Semantic
154 similarity then can be employed to assess how closely related two anatomical concepts are in
155 the ontology, a metric that can be used to link characters in a character matrix to a

156 ontologically structured hierarchy, thus providing the backbone for comparisons among data
157 subsets (Fig. 2a).

158 The approach advocated here combines elements of information theory with ontology
159 knowledge allowing one to investigate what sort of processes may structure probabilities in
160 the tree space of the posterior distribution of tree topologies (Fig. 2b). BPI provides a measure
161 of how much uncertainty there is in the posterior inferred from a data subset: lower BPI
162 means more possible trees with probability scattered across them (e.g., Fig. 2b: DF); higher
163 BPI means fewer possible trees with probability concentrated in some of them (e.g., Fig. 2b:
164 PVF or PCF). Phylogenetic dissonance provides a measure of how congruent posterior
165 distributions of trees inferred from different data subsets are: lower dissonance means that a
166 similar set of trees with similar probabilities are present in the posteriors (e.g., Fig. 2b: PVF
167 vs. PCF); higher dissonance means that there is low or no overlap among the posteriors (e.g.,
168 Fig. 2b: DF vs. IO). If subsets are defined based on organismal anatomy and the patterns of
169 phylogenetic dissonance observed in the tree space of the posterior (Fig. 2b) reflect the
170 ontological hierarchy (Fig. 2a), then one can ask if anatomy/development may play a role in
171 explaining phylogenetic information in the data. In other words, ontology knowledge
172 structures phylogenetic information in this case (i.e., there is *semantic signal*). Alternatively,
173 if groups of unrelated anatomy entity concepts (i.e., low semantic similarity) provide
174 congruent trees and such trees are congruent with the ‘true’ species phylogeny (Fig. 1a), then
175 such entities are just following the common species history. Finally, if groups of unrelated
176 anatomy entity concepts provide congruent trees that are different from the species tree (Fig.
177 1b), then other processes may be suspected (e.g., concerted convergence).

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180

181 **FIGURE 2.** Diagrammatic representation of the relationship between ontology structure,
182 represented as a clustering dendrogram, and a hypothetical posterior tree space. (a) Ontology
183 hierarchy of anatomy entity concepts referring to data subsets used to infer posterior
184 distribution of trees (only one tree shown above each term). The hierarchy is represented as a
185 clustering dendrogram based on semantic similarity distances among anatomy entity concepts
186 (b) Representation of a hypothetical posterior tree space. Each circle indicate a discrete tree

187 topology. Shade intensity is proportional to the posterior probability of each topology. Dotted
188 ellipses indicate the hypothetical area of the tree space occupied by inferred trees in the
189 posterior of some data subsets. Abbreviations: DF, dorsal fin; DEN, dentary; IO, infraorbital;
190 MX, maxilla; PCF, pectoral fin; PMX, premaxilla; PVF, pelvic fin. For colors, please refer to
191 the online version of this paper available at [XXX](#).
192

193 In this study we evaluated the phylogenetic information content of ontology-annotated
194 character matrices by measuring BPI and phylogenetic dissonance applied to morphological
195 data in phylogenetic inferences. We applied this approach to two datasets representing
196 disparate animal groups for which well-established anatomy ontologies are available: bees
197 (Hexapoda: Hymenoptera: Apoidea) and characiform fishes (Actinopterygii: Ostariophysi:
198 Characiformes). Within the characiform fishes, we further targeted specific evolutionary
199 questions concerning miniaturization, which is predicted to result in convergent evolution
200 among certain data subsets. We propose a new framework for evaluating alternative
201 hypotheses for the sets of ontological relationships that best explain phylogenetic information
202 across ontology-annotated anatomical data subsets (i.e., *semantic signal*). This framework is
203 not limited to the Bayesian information metrics used here, and it can be a general approach to
204 understanding how ontologies may structure phylogenetic information inferred from
205 anatomical data and investigating whether morphologically related entities show similar tree-
206 like histories due to a shared phylogeny (i.e., *phylogenetic signal*) or other process such as
207 concerted convergence. We have made our implementation of this methodology available in
208 the new R package *ontobayes* (<https://github.com/diegosasso/ontobayes>).
209

210 MATERIAL AND METHODS

211 *Theoretical Background*

212 *Definitions.* Throughout this paper, we employed a few terms with varying usage in the
213 literature. ‘Dependency’ (e.g., either anatomical, morphological, or structural) is used in the
214 same sense as ‘ontological dependency’ (Vogt 2018a) to describe the types of relationships

215 when the absence/presence of one anatomical entity determines the absence/presence or
216 condition of another. The terms ‘trait’ and ‘character’ are used mostly interchangeably to
217 mean “any recognizable phenotypic unit from organisms”. Here, ‘character’ is used to
218 specifically refer to phenotypic units that are variable across organisms and used as input data
219 in phylogenetic analyses. We make a distinction in the use of the terms ‘dendrogram’ and
220 ‘tree’, despite the former including the latter. ‘Dendrogram’ or ‘clustering dendrogram’ is
221 used here to refer to any tree-like hierarchical diagram depicting relationships among anatomy
222 ontology terms. ‘Tree’ or ‘phylogenetic tree’ is reserved to the hierarchical diagrams
223 depicting relationships among species. ‘Topology’ is used to refer to the ordering of the
224 hierarchy among leaves in such tree-like diagrams, without respect to edge length. ‘Term’ is
225 used to refer to the labels applied to real anatomical entities represented as concepts in an
226 anatomy ontology. ‘Data subset’ or ‘partition’ is used to refer to groups of traits/characters
227 annotated with or descended from a particular ontology term/concept.

228

229 *Ontologies.* Ontologies are structured controlled vocabularies formalizing relationships
230 among concepts in a specific domain of knowledge, for example, vertebrate (Dahdul et al.
231 2012; Haendel et al. 2014) and hymenopteran anatomy (Yoder et al. 2010). Concepts can be
232 expressed by terms linked to or defining organismal anatomical entities (e.g., ‘opercle’ from
233 the Uberon anatomy ontology, Mungall et al. 2012; Haendel et al. 2014) or phenotypic
234 qualities (e.g., ‘triangular’ from the Phenotype and Trait Ontology, Gkoutos et al. 2005), and
235 phenotypes can be described using the Entity-Quality syntax (e.g., E: ‘opercle’, Q:
236 ‘triangular’) (Mungall et al. 2010; Balhoff et al. 2010; Dahdul et al. 2010a, 2012).
237 Relationships among concepts can be of various kinds (e.g., *part_of*, *is_a*, *develops_from*) and
238 different logical relations may be included to build knowledge graphs with relevant structural

239 or developmental information about organismal traits (e.g., Dahdul et al. 2010b; Mabee et al.
240 2012).

241 Ontological knowledge can be explored in different ways to summarize information
242 on structural dependencies among anatomical entities instantiating ontology concepts. One
243 possibility is to use semantic similarity measures to build a dendrogram depicting distances
244 among anatomy entity concepts (Fig. 2a). Semantic similarity can be assessed using different
245 metrics such as edge-based distances (e.g., *Jaccard*), node-based information content (e.g.,
246 *Resnik*), or hybrid metrics (e.g., Hybrid Relative Specificity Similarity)(Pesquita et al. 2009;
247 Manda and Vision 2018). Different metrics can capture alternative and/or complementary
248 properties of the ontology. The types of relations included as well as the ontology structure
249 itself can influence the overall similarity values between concepts (Pesquita et al. 2009;
250 Manda and Vision 2018). Another possibility is to use ontological knowledge to explicitly
251 account for anatomical dependencies among individual traits when specifying models of
252 character evolution (Tarasov 2019, 2020; Tarasov et al. 2019). This can be achieved by
253 constructing models of discrete trait evolution enabling ontology-aware transition matrices
254 through structured Markov models equipped with hidden states (Tarasov 2019). In this work,
255 we focused on the first way of exploring ontology knowledge.

256

257 *Bayesian phylogenetic information.* BPI is the amount of information about phylogenetic tree
258 topology inferred from the data. It is measured as the difference in entropy between prior and
259 posterior probability distributions on phylogenetic tree topologies (Lewis et al. 2016). In this
260 context, entropy can be interpreted as a measure of uncertainty and is inversely proportional
261 to information. If data provides no information in favor of any phylogenetic tree topology,
262 then entropy (and uncertainty) is maximal and all possible trees are equiprobable (assuming a
263 discrete uniform prior). Thus, phylogenetic information inferred from data will make some

264 phylogenetic tree topologies from the prior more probable than others resulting in a
265 concentrated posterior (Lewis et al. 2016).

266 Comparing BPI from different subsets allows the estimation of the amount of
267 informational conflict between posterior probability distributions of phylogenetic tree
268 topologies—i.e., phylogenetic dissonance (Lewis et al. 2016; Neupane et al. 2019). In this
269 study, we asked whether ontology structures Bayesian phylogenetic information for
270 phylogenetic tree topology (see also Lewis et al. 2016; Neupane et al. 2019; Porto et al. 2021),
271 although similar questions could be asked for other types of information (e.g., regarding
272 ancestral states for discrete characters; Borges et al. 2019). Since the prior on phylogenetic
273 tree topology for a dataset with a given number of taxa is the same as for all its possible
274 subsets—for unrooted dichotomous labeled phylogenetic trees it depends only on total
275 number of taxa—BPI from different data subsets can be compared to assess their individual
276 informational contributions in phylogenetic analyses (e.g., Neupane et al. 2019; Porto et al.
277 2021). Therefore, BPI and phylogenetic dissonance provide straightforward measures for
278 assessing how much agreement or disagreement there is between the posterior distributions of
279 phylogenetic tree topologies from two or more data subsets. We use these statistics to
280 investigate how the ontology structure translates as congruence or dissonance in phylogenetic
281 information provided by different subsets.

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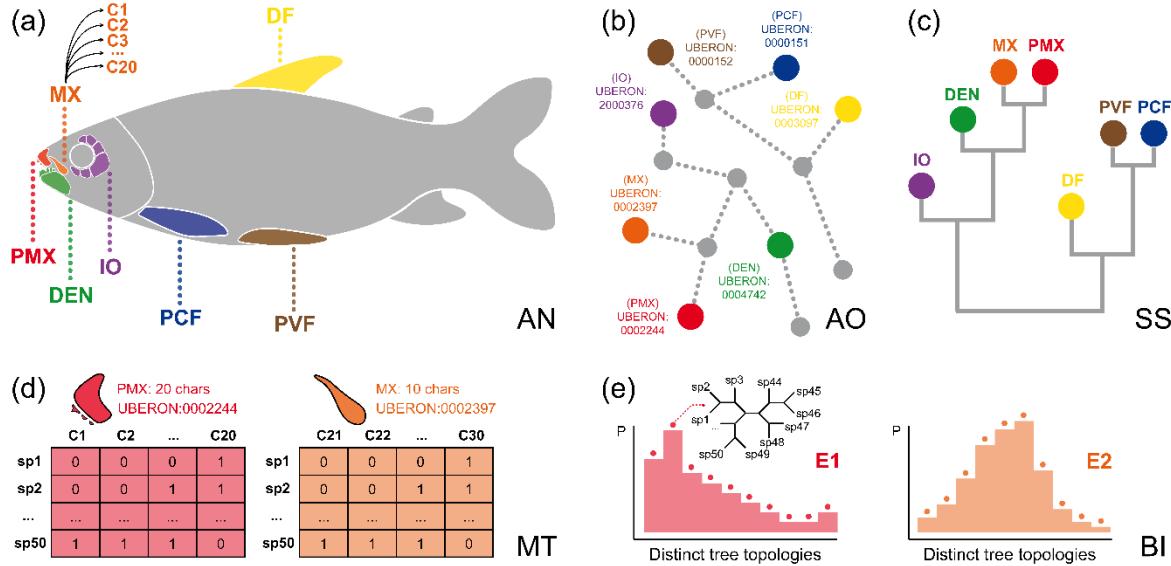
283 *The Ontobayes Approach*

284 To measure phylogenetic information and dissonance, we carried out four main steps using R
285 (R Core Team 2021), MrBayes (Ronquist et al. 2012), and Galax (Lewis et al. 2016) in an
286 implementation of our analysis, which we call *ontobayes*. In brief, we aggregate ontology-
287 annotated characters into subsets based on anatomical terms and use phylogenetic analyses of
288 these subsets in MrBayes to obtain posterior samples of phylogenetic tree topologies. The

289 samples are then used to calculate the information theory metrics (i.e., BPI and phylogenetic
290 dissonance) in Galax to compare different subsets. All functions, examples, and
291 documentation for the *ontobayes* R package are available at
292 <https://github.com/diegosasso/ontobayes> and in the online Supplementary Material available
293 on Dryad.

294 We incorporated ontological knowledge about organismal anatomy (Fig. 3a) by
295 building data subsets (Fig. 3d) grouping characters based on ontology term annotations (Fig.
296 3b) and structuring relationships among ontology concepts as clustering dendrograms (Fig.
297 3c). We based dendrograms on distance matrices from measures of semantic similarity using
298 functions from *rphenoscape* (<https://github.com/phenoscape/rphenoscape>) (Fig. 3c, hereafter
299 ‘semantic similarity dendrogram’) or phylogenetic dissonance (hereafter ‘dissonance
300 dendrogram’). We evaluated two alternative ways of constructing dendrograms based on: (1)
301 all available terms annotated to characters in a given character matrix (ALL) and (2) a smaller
302 selection (‘profile’) of preferred terms (PROFILE), which allow for specific investigation of
303 terms of particular research interest. We estimated BPI and phylogenetic dissonance in Galax
304 (i) among different MCMC runs from the same data subset and (ii) from different data subsets.
305 The former analysis assess the topological convergence and information content (Lewis et al.
306 2016), while the latter measures concordance or conflict among two or more distinct data
307 subsets. Entropy measures in Galax (Fig. 3e, e.g., E1 and E2) were then be used to estimate
308 information content and conflict by assessing uncertainty in posterior probability distributions
309 (see discussions in Lewis et al. 2016; Neupane et al. 2019; Porto et al. 2021).

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312

313 **FIGURE 3.** Diagrammatic representation of main steps of the *ontobayes* analysis. (a) Ontology
 314 terms referring to anatomical entities are linked to characters in a matrix using expert
 315 judgment. (b) Terms in the ontology are related to other terms by logical relations (e.g., *is_a*,
 316 *part_of*) which can be represented as a graph. (c) Semantic similarity metrics derived from
 317 such a graph (e.g., *Jaccard*, *Resnik*) can be employed to build a clustering dendrogram for
 318 terms. (d) The structure of such a dendrogram can then be used to guide comparison of
 319 subsets of characters linked to the same or related ontology terms. (e) Each subset is used to
 320 produce posterior probability distributions of phylogenetic tree topologies which are used to
 321 estimate Information Theory metrics (i.e., entropy, information, dissonance). Abbreviations:
 322 AN, organismal anatomy; AO, anatomy ontology; BI, Bayesian inference; C1...C30,
 323 characters in a matrix; DF, dorsal fin; DEN, dentary; E1...E2, entropy of posterior
 324 distributions; IO, infraorbital; MT, character matrices; MX, maxilla; PCF, pectoral fin; PMX,
 325 premaxilla; PVF, pelvic fin; sp1...sp50, species in a matrix; SS, semantic similarity
 326 dendrogram. For colors, please refer to the online version of this paper available at [XXX](#).
 327

328 *Empirical Analyses*

329 We analyzed how ontology structures phylogenetic information with two datasets
 330 representing disparate animal groups: bees and characiform fishes. The two groups were
 331 selected for this study since well-established anatomy ontologies are already available for
 332 them (bees and other hymenopteran insects: Hymenoptera Anatomy Ontology, HAO, Yoder
 333 et al. 2010; vertebrate animals: Uberon anatomy ontology, Mungall et al. 2012; Haendel et al.
 334 2014) and comprehensive character matrices could be annotated with ontology terms based on
 335 the authors' expertise. The BEE dataset was modified from Porto et al. (2021), which includes

336 corbiculate bees and related taxa (Hexapoda: Hymenoptera: Apidae). The original matrix was
337 reduced to contain only 10 bee species because Bayesian phylogenetic information content
338 estimation is less reliable when the number of taxa (and thus possible phylogenetic tree
339 topologies) is large (Lewis et al. 2016). Two species representing each of the four corbiculate
340 bee tribes (i.e., Apini, Bombini, Euglossini, and Meliponini) were selected, plus two outgroup
341 taxa (Centridini: *Epicharis* and Anthophorinae: *Anthophora*). The taxon sampling represents
342 the diversity among the main lineages of Apinae bees (e.g., see Porto et al. 2021). The final
343 dataset contained a total of 209 informative characters, each annotated with anatomical terms
344 from HAO (see supporting data in the online Supplementary Material available in Dryad).
345 This dataset was first analyzed under the PROFILE alternative of subset construction, which
346 is based on pre-defined groups of selected ontological terms (i.e., ‘profiles’). Six groups of
347 terms from HAO were chosen so as to assess the information content and dissonance within
348 and across data subsets representing groups of anatomical entities in distinct body regions
349 from the bee anatomy. The anatomical terms were selected so as to represent the main
350 morpho-functional regions in the body of a typical apocritan Hymenoptera. The groups of
351 selected terms were: 1. Mouthparts: labrum, mandible, maxilla, labium, and sitophore; 2.
352 Head: cranium and tentorium; 3. Mesosoma: prothorax, mesothorax, and metathorax; 4. Legs:
353 fore, mid, and hind legs; 5. Wings: fore and hind wings; 6. Metasoma: male and female
354 genitalia. In addition to these pre-defined profiles, we analyzed this dataset under the ALL
355 alternative of subset construction to obtain a dissonance dendrogram, which represents
356 relationships among all ontological terms annotated to characters in the matrix by estimating
357 phylogenetic dissonance for all pairwise comparisons among data subsets (see supporting data
358 in the online Supplementary Material available in Dryad).

359 The FISH dataset was obtained from Dillman et al. (2016) and includes information
360 for four families of anostomoid fishes in the order Characiformes (Actinopterygii):

361 Ostariophysi: Characiformes). The original matrix was reduced so as to contain only 10 taxa
362 and retaining 463 characters, each annotated with anatomical terms from the Uberon ontology
363 (see supporting data in the online Supplementary Material available in Dryad). Two or more
364 species representing the four anostomoid families (i.e., Anostomidae, Chilodontidae,
365 Curimatidae, and Prochilodontidae) were selected, along with one outgroup taxon
366 (Parodontidae: *Parodon*). The taxon sampling represents the diversity among the main
367 lineages of anostomoid fishes (e.g., see Dillman et al. 2016). This dataset was analyzed under
368 the ALL alternative of subset construction. It was first used to compare alternative ways of
369 representing the relationships among subsets of ontological terms (e.g., phylogenetic
370 dissonance and semantic similarity dendograms) to assess congruence between ontology
371 structure and phylogenetic information. We then evaluated (1) the information content of
372 individual data subsets defined as groups of characters annotated to the same ontological
373 term; (2) information content and dissonance among distinct subsets defined by different
374 ontological terms; and (3) clade-specific information components provided by each subset to
375 nodes in a given reference phylogenetic species tree. The reference species tree was inferred
376 using all 463 characters for the 10 fish species sampled and represents the phylogenetic
377 knowledge acquired when the information from all characters annotated to all ontological
378 terms is considered together. The dataset was also used to investigate whether subsets of data
379 might be ontologically related to particular terms (in this case, as an example, all terms that
380 are *part_of* ‘dermatocranium’).

381 Within characiform fishes, miniaturization has occurred multiple times and may result
382 in convergent character states for sets of traits. To evaluate whether the degree to which
383 characters respond to these convergent selection pressures is structured by ontology we
384 assembled a modified third dataset, the MINI dataset, from Mirande (2019). We focused on
385 10 species of characiform fishes that had multiple convergent miniatures and retained 453

386 characters, each annotated with anatomical terms from the Uberon ontology (see supporting
387 data in the online Supplementary Material available in Dryad). Specifically, taxon selection
388 included: four miniature fishes (body size < 26mm *sensu* Weitzman and Vari 1988) and six
389 non-miniature fishes representing four different lineages of Characidae and two outgroups.
390 Each characid lineage was represented by a miniature and a non-miniature species. To assess
391 convergence, a reference phylogenetic tree was inferred that constrained all miniatures to a
392 monophyletic grouping. Clade-specific information components were then obtained for all
393 subsets of characters to determine whether the ontology structures which traits are more
394 informative about miniaturization phenotypes, and which traits follow the species tree.

395 Finally, we further evaluated whether the ontology structures phylogenetic information
396 and dissonance across characters by conducting comparisons of ontology-based subsets and
397 randomly resampled sets of characters from the original FISH dataset. Six terms from the
398 Uberon ontology annotated to multiple characters in the FISH dataset and representing
399 different anatomical entities (i.e., fish bones) were chosen: 1. Premaxilla (PMX, 8 chars), 2.
400 Maxilla (MX, 14 chars), 3. Dentary (DEN, 8 chars), 4. Infraorbital (IO, 11 chars), 5.
401 Epibranchial bone (EB, 15 chars), and 6. Ceratobranchial bone (CB, 10 chars). For each term,
402 100 different subsets of the same size were produced by randomly sampling characters from
403 the original FISH dataset. These resampled subsets were compared to the ontology-based
404 (hereafter ‘standard’) subsets by measuring BPI and phylogenetic dissonance. Ontological
405 relationships among selected terms were represented as a semantic similarity dendrogram that
406 was then employed to guide sequential pairwise comparisons between data subsets based on
407 terms with successive increasing distances within the ontology (i.e., decreasing semantic
408 similarity) adopting one term as a fixed reference (i.e., PMX, premaxilla).

409 Posterior samples of phylogenetic tree topologies were obtained running MCMC
410 analyses in MrBayes (Ronquist et al. 2012) with two runs and four chains, for 1.0×10^7

411 generations, sampling every 1000th generation, and discarding the first 25% as burn-in. The
412 Mk+G model was employed with the following priors and parameters: 1. Tree topology prior:
413 Discrete Uniform (1, |T|); 2. Branch lengths prior: Exponential (10); 3. Discrete Gamma
414 shape: Exponential (1); 4. State frequencies: Symmetric Dirichlet (infinity); 5. Coding bias:
415 *variable* (except for the FISH dataset, which was set to *all*). Scripts to generate all NEXUS
416 files and run analyses of individual data subsets were produced using the functions available
417 in *ontobayes*.

418

419 **RESULTS**

420 *Analyses of the BEE Dataset.*

421 Results from PROFILE analyses of the BEE dataset are shown in Table 1. Posterior coverage,
422 i.e., the fraction of the total posterior probability distribution actually represented in the
423 posterior sample of phylogenetic tree topologies (Lewis et al. 2016), for individual data
424 subsets ranged from 51.0% for ‘mid leg’ to 99.7% for ‘male genitalia’; for profiles it ranged
425 from 68.8% for ‘legs’ to 94.4% for ‘metasoma’. Such values indicate overall reasonable
426 coverage (at least 50%) given that the number of possible phylogenetic tree topologies grows
427 steeply with the increase in the number of taxa. BPI for individual data subsets ranged from
428 31.7% for ‘labrum’ to 80.7% for ‘male genitalia’ and for profiles from 39.6% for ‘legs’ to
429 62.1% for ‘metasoma’. Phylogenetic dissonance between different runs of MCMC for most
430 individual data subsets was close to zero (0.1~0.7%) indicating topological convergence in
431 the posterior; the exceptions were ‘labrum’ and ‘mid leg’ showing slightly higher values
432 (1.1% and 1.3% respectively). Dissonance for profiles ranged from 8.5% for ‘head’ to 14.7%
433 for ‘mesosoma’ indicating substantial informational conflict among data subsets within
434 profiles. A clustering dendrogram depicting hierarchical relationships among ontological

435 terms annotated to individual data subsets included in PROFILE analyses is shown in Figure
436 S1 (Supplementary Material: Fig. S1).

437

438 **TABLE 1.** Results from PROFILE analyses of the BEE dataset.

439

Data subset	Coverage ^a	Information ^b	Dissonance ^c
Mouthparts			
Labrum	60.23	31.73	1.11
Mandible	94.39	60.70	0.38
Maxilla	96.29	58.69	0.27
Labium	97.45	65.60	0.14
Sitophore	89.16	55.67	0.55
Run 1	85.26	47.60	13.61
Run 2	85.31	47.49	13.83
Mean	85.28	47.54	13.72
Head			
Cranium	97.42	69.55	0.17
Tentorium	82.71	47.00	0.63
Run 1	87.34	54.64	8.39
Run 2	86.86	54.57	8.62
Mean	87.10	54.61	8.51
Mesosoma			
Prothorax	99.30	75.62	0.13
Mesothorax	97.81	67.56	0.22
Metathorax	85.32	49.73	0.66
Run 1	91.93	58.25	14.61
Run 2	91.96	58.39	14.78
Mean	91.94	58.32	14.70
Legs			
Fore leg	83.36	50.07	0.49
Mid leg	51.00	30.25	1.28
Hind leg	95.01	59.14	0.33
Run 1	69.23	39.61	12.04
Run 2	68.34	39.67	12.05
Mean	68.78	39.64	12.05
Wings			
Fore wings	75.31	40.77	0.55
Hind wings	91.23	55.19	0.37
Run 1	71.45	42.24	10.37
Run 2	71.29	42.23	10.38
Mean	71.37	42.23	10.37
Metasoma			
Female genitalia	92.07	52.24	0.36
Male genitalia	99.70	80.85	0.14
Run 1	94.44	62.19	11.84
Run 2	94.31	62.09	11.94
Mean	94.37	62.14	11.89

440

441 ^a ϕ , estimated posterior coverage, expressed as percentage of maximum, as defined in
442 Lewis et al. (2016).

443 ^b *BPI*, estimated Bayesian phylogenetic information content, expressed as percentage of
444 maximum, as defined in Lewis et al. (2016).

445 ^c *D*, estimated phylogenetic dissonance, expressed as percentage of maximum, as defined in
446 Lewis et al. (2016).

447

448 The dissonance dendrogram shows that data subsets included *a priori* in the same
449 profile according to prior expert judgement about bee's anatomy (Table 1) were not
450 necessarily the ones less dissonant among themselves (Supplementary Material: Fig. S1). For
451 example, subsets included in the 'mouthparts' profile (i.e., 'labrum', 'mandible', 'maxilla',
452 'labium', and 'sitophore') were not clustered in the dissonance dendrogram (Supplementary
453 Material: Fig. S1: e.g., 'labrum' groups with 'metathorax' and 'mandible' with 'fore leg').
454 This indicates that BPI content estimated from different subsets within profiles shows
455 significant conflicting signal, i.e., information for alternative sets of phylogenetic tree
456 topologies in the posterior distribution. Patterns observed in the dissonance dendrogram
457 (Supplementary Material: Fig. S1) agreed with results shown in Table 1 indicating conflict
458 among data subsets within profiles (phylogenetic dissonance $>> 5\%$).

459 Results from ALL analyses of the BEE dataset (Supplementary Material: Fig. S2 and
460 Table S1) showed similar patterns. Clustering of ontological terms annotated to data subsets
461 based on phylogenetic dissonance does not reflect structural dependencies among anatomical
462 entities of the bee anatomy. For example, BPI inferred from morphologically closely related
463 entities such as 'stipital sclerite', 'lacinial lobe', and 'galea' (all *part_of* a bee 'maxilla') were
464 highly dissonant among subsets (i.e., terms far apart in the dissonance dendrogram) whereas
465 that of some unrelated entities such as 'flabellum' (*part_of* 'labium') and 'female genitalia'
466 (*part_of* 'metasoma') were often less dissonant. BPI content inferred from individual subsets
467 varied greatly in the ALL analyses of the BEE dataset as well (Supplementary Material: Table
468 S1 and Fig. S2: barplots). Relative information, measured as the BPI of an individual subset
469 divided by the mean BPI across all subsets, was particularly high for many subsets
470 instantiating anatomical entities from the mouthparts (e.g., 'sitophore', 'labrum', 'stipes'),
471 prothorax (e.g., 'profurcasternum', 'probasisternum', 'propleuron'), and metasoma (e.g.,

472 ‘male genitalia’, ‘female genitalia’) of bees (Supplementary Material: Fig. S2: bar heights
473 higher than 1.0). BPI content for individual data subsets shown in Table S1 (Supplementary
474 Material: Table S1) indicate considerably low phylogenetic information (< 25%) for at least
475 half of them, also reflected in the higher phylogenetic dissonance values between different
476 MCMC runs.

477

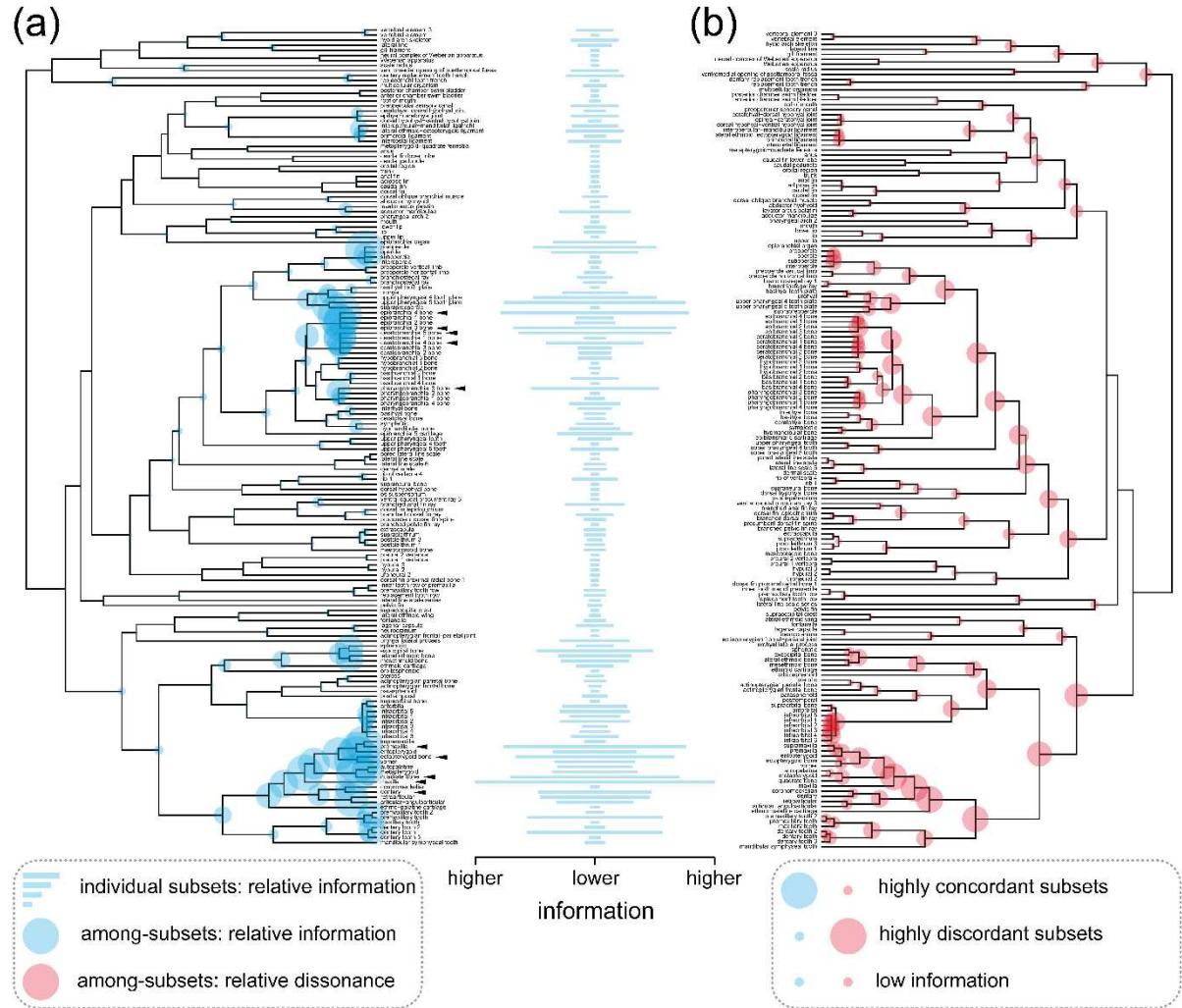
478 *Analyses of the FISH Dataset.*

479 As shown in Figures S3 and S4 (Supplementary Material: Figs S3 and S4), overall
480 relationships among ontology terms were quite different between the semantic similarity and
481 dissonance dendrograms indicating that phylogenetic information is not always structured by
482 ontological knowledge and closely related terms in the ontology (i.e., semantically similar) do
483 not always correspond to data subsets with more congruent phylogenetic information (i.e.,
484 lower phylogenetic dissonance). Relationships based on semantic similarity (Supplementary
485 Material: Fig. S3), which reflect distances among concepts in the anatomy ontology, can be
486 compared to relationships based on phylogenetic dissonance (Supplementary Material: Fig.
487 S4), which reflect the degree of phylogenetic congruence or conflict among the posterior
488 distributions of phylogenetic tree topologies obtained from the analyses of the subsets
489 annotated to ontology terms. For example, the dissonance dendrogram indicate the following
490 relationships among three particular anatomy terms: (‘premaxilla’ + ‘maxilla’) + ‘dentary’.
491 This means that the posterior distributions of phylogenetic tree topologies obtained from the
492 analyses of all characters annotated to the term ‘premaxilla’ and all characters annotated to
493 the term ‘maxilla’ are more similar (i.e., include a more similar set of phylogenetic trees with
494 similar posterior probabilities) than either is to the posterior distribution obtained from the
495 analysis of all characters annotated to the term ‘dentary’. In other words, the phylogenetic

496 information inferred from premaxillary and maxillary characters is more congruent; that for
497 premaxillary and dentary or maxillary and dentary characters is less.

498 BPI content of individual data subsets and patterns of BPI and phylogenetic
499 dissonance among-subsets mapped onto the semantic similarity dendrogram obtained for the
500 FISH dataset varied greatly with most subsets presenting relatively low information (Fig. 4:
501 middle column barplots). However, two major clusters of terms in the semantic similarity
502 dendrogram (indicated by arrowheads) represent groups of relatively highly informative
503 individual data subsets (e.g., some bones from the epibranchial and ceratobranchial series,
504 maxilla, premaxilla, dentary, ectopterygoid and quadrate bones etc.). Relative information
505 among-subsets, measured as among-subset BPI divided by mean among-subset BPI across all
506 nodes of the semantic similarity dendrogram, was especially higher in some sectors of the
507 dendrogram (Fig. 4a: blue circles) and decreased drastically towards deeper nodes (Fig. 4a:
508 blue circles). Relative dissonance among-subsets, measured in a similar way, showed a
509 similar but opposing pattern (as expected) with overall increase in values towards deeper
510 nodes (Fig. 4b: red circles).

511



512

513

514 **FIGURE 4.** Bayesian phylogenetic information content for all anatomical entities linked to
515 Uberon terms in the FISH dataset. Clustering dendrograms in (a) and (b) are obtained from
516 pairwise semantic similarity between terms converted to a distance matrix. Barplots in middle
517 column show information content of individual trait subsets defined by ontology terms
518 relative to mean information across all subsets. Filled circles in trait dendrograms show (a)
519 Bayesian phylogenetic information content and (b) phylogenetic dissonance among trait
520 subsets defined by the ontology terms subtended by each node relative to respective mean
521 values across all subsets. Bar lengths and circles have no absolute scale and are proportional
522 to the relative maximum amount of (a) information or (b) dissonance observed. Bottom left
523 and right boxes contain explanatory diagrams on how to interpret results in this figure. For
524 colors, please refer to the online version of this paper available at **XXX**.
525

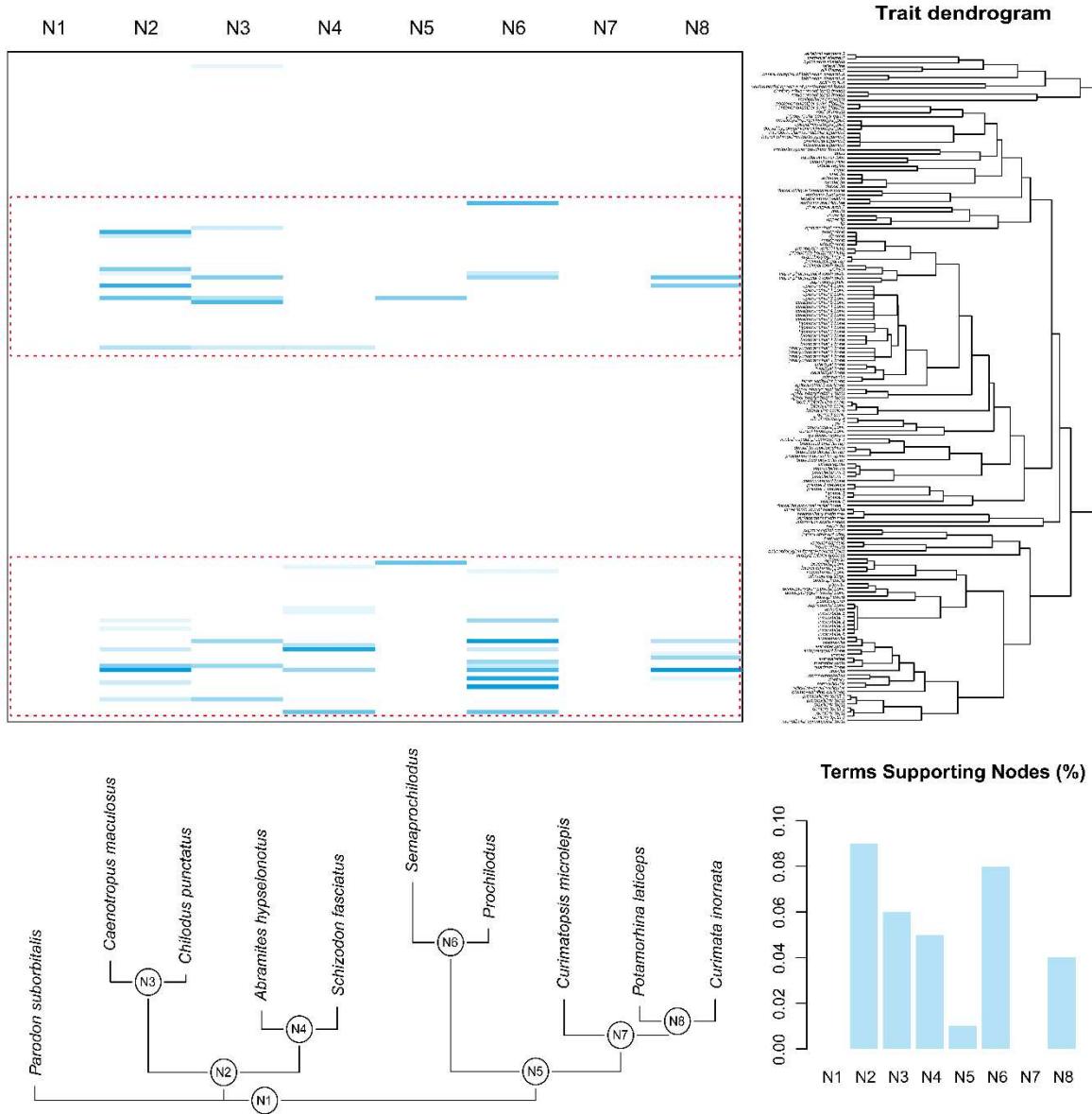
526 Patterns of among-subset information and dissonance are better understood in
527 conjunction, as explained in the bottom-right box in Figure 4. Clusters of data subsets
528 providing highly congruent phylogenetic information are also expected to present relatively

529 higher among-subset relative information (Fig. 4a: large blue circles) and lower dissonance
530 (Fig. 4b: small red circles) since they should represent similar posterior distributions of
531 phylogenetic tree topologies (e.g., Fig. 2b: PCF and PVF). On the other hand, if data subsets
532 provide highly conflicting information, then the opposite will be true, with relatively lower
533 among-subset relative information (Fig. 4a: small blue circles) and higher dissonance (Fig.
534 4b: large red circles) (e.g., Fig. 2b: DF and IO). If most datasets provide little to no
535 information at all, then both among-subset relative information and dissonance will be
536 relatively lower since they should represent mostly flat, broadly overlapping, posterior
537 distributions of phylogenetic trees. More complex scenarios, however, are usually found, with
538 many clusters grouping multiple data subsets with varying degrees of information content and
539 only partly overlapping posterior distributions of phylogenetic trees (e.g., Fig. 2b: PCF and
540 DF) thus resulting in more ambiguous patterns of among-subsets relative information and
541 dissonance, as observed for many nodes in Figure 4 (blue and red circles). Results were
542 further inspected as phylogenetic tree topology trace plots (as available in the R package
543 RWTY, Warren et al. 2017) to help assess degree of overlap between posterior distributions
544 and better understand patterns of among-subsets information and dissonance. Some examples
545 contrasting posterior distributions of phylogenetic tree topologies from both MCMC runs
546 from the same data subset and from different subsets with congruent or conflicting
547 phylogenetic information are provided in Figures S5 and S6, respectively (Supplementary
548 Material: Figs S5 and S6).

549 Clade-specific phylogenetic information inferred from data subsets in the FISH dataset
550 demonstrate that most phylogenetic information for the particular reference species tree
551 obtained from the analysis of the full dataset (Fig. 5, bottom) is inferred from two major
552 clusters of data subsets (Fig. 5, heatmap, dashed boxes) as indicated in the semantic similarity
553 dendrogram (Fig. 5, right): one including bones from epibranchial, ceratobranchial, and

554 pharyngobranchial series (Fig. 5, trait dendrogram, top cluster); and another including bones
555 from maxilla, premaxilla, dentary, and infraorbital series, among others (Fig. 5, trait
556 dendrogram, bottom cluster). With the exception of the first node (Fig. 5, species tree, bottom,
557 N1), which was enforced due to rooting, only one node in the reference phylogenetic species
558 tree received no support at all (Fig. 5, species tree, bottom, N7); all other nodes received
559 variable amount of support from different subsets in both clusters (Fig. 5, top-left, heatmap;
560 e.g., N2–N6; shade intensity proportional to posterior probability). The proportion of data
561 subsets supporting each node in the phylogenetic species tree also varied (Fig. 5, bottom-right,
562 barplots), with about only 1% of all subsets supporting N5 and between 4% and 9%
563 supporting other nodes. It was also possible to investigate if the two inferred clusters of data
564 subsets shared underlying ontological concepts. For example, we filtered all ontology terms
565 defining subsets that are *part_of* ‘dermatocranum’ (Supplementary Material: Fig. S7: orange
566 shaded rows in the heatmap) and found that information only from bones from the fish
567 dermatocranum supported N5 (Supplementary Material: Fig. S7, species tree, bottom, N5)
568 and most non-dermatocranum bones supported N2 and N4 (Supplementary Material: Fig. S7,
569 species tree, bottom, N2 and N4).

570



585 Results from the analysis of the MINI dataset (Supplementary Material: Fig. S8) showed little
586 phylogenetic information to tree topology that could be useful to address the particular
587 question about miniaturization in this sample of characiform fishes. Only a few data subsets
588 (about 1%) provided information to N5, the clade enforcing the grouping of all miniature
589 fishes (Supplementary Material: Fig. S8, species tree, bottom, N5). Most data subsets (about
590 7%) provided information to N2, the clade including all Characidae (Supplementary Material:
591 Fig. S8, species tree, bottom, N2). No data subset provided information to N6 and N7
592 (Supplementary Material: Fig. S8, species tree, bottom, N6–N7), subclades of the miniature
593 fishes clade. The majority of data subsets informative to nodes recovered in the reference
594 phylogenetic species tree (Supplementary Material: Fig. S8, species tree, bottom, N2–N5)
595 were annotated to ontology terms mostly related to anatomical entities comprising particular
596 tooth rows from jaw bones (e.g., ‘premaxillary tooth row’, ‘maxillary tooth row’, ‘dentary
597 tooth row’), with ‘premaxillary tooth row’ supporting the miniature fishes clade.

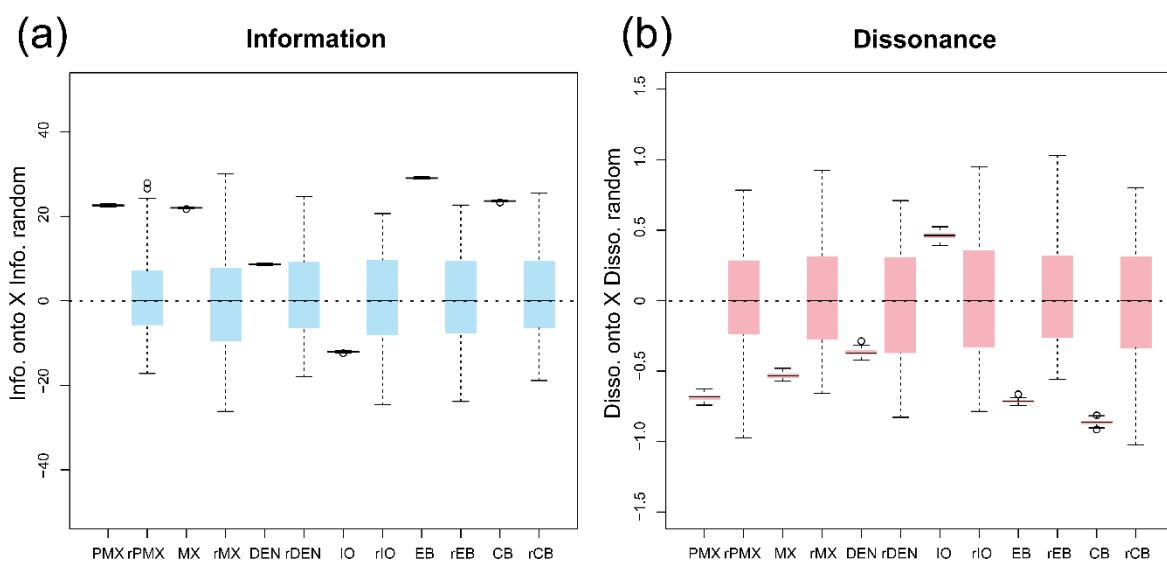
598

599 *Resampling Analyses.*

600 Resampling analyses show that mean values of BPI and phylogenetic dissonance were higher
601 and lower, respectively, in datasets based on ontology term annotations compared to those
602 composed by randomly resampling characters—strongly supporting that some ontology-based
603 subsets carry shared phylogenetic information. BPI estimated for standard subsets were
604 almost always higher than their respective resampled counterparts (Fig. 6a: e.g., PMX, MX,
605 EB, CB). As expected, the opposite pattern was observed for phylogenetic dissonance, with
606 most standard subsets showing lower values (Fig. 6b). A semantic similarity dendrogram for
607 the selected ontology terms recovered two clusters, one for ‘premaxilla’ + ‘maxilla’ +
608 ‘dentary’ + ‘infraorbital’ and another for ‘ceratobranchial bone’ + ‘epibranchial bone’
609 (Supplementary Material: Fig. S9). Results of pairwise comparisons between data subsets

610 with estimates of phylogenetic dissonance obtained for standard and resampled subsets are
611 shown in Figure S10 (Supplementary Material: Fig. S10). Note that estimates for comparisons
612 between standard subsets show a trend of increasing phylogenetic dissonance (Supplementary
613 Material: Fig. S10: e.g., PMX-MX, PMX-DEN, PMX-IO, PMX-EB etc.) when datasets
614 annotated to increasing distantly related ontology terms were compared (Supplementary
615 Material: Fig. S9).

616



619 **FIGURE 6.** Boxplots showing estimated (a) Bayesian phylogenetic information and (b)
620 phylogenetic dissonance across replicated analyses for standard data subsets relative to
621 resampled data subsets. Values above the dotted line indicate values higher than the median
622 of the respective resampled data subsets. Note that information is higher and dissonance is
623 lower for all ontology-based data subsets except IO than random subsets sampled of the same
624 size, but without respect to ontology. Abbreviations: CB, ceratobranchial bone; DEN,
625 dentary; EB, epibranchial bone; IO, infraorbital; PMX, premaxilla; MX, maxilla. The “r”
626 prefix denote resampled subsets. For colors, please refer to the online version of this paper
627 available at [XXX](#).

628

629 DISCUSSION

630 Ontologies bridge different domains of knowledge across life sciences (e.g., anatomy,
631 development, genetics, behavior, ecology) allowing data integration within and across

632 databases (Mabee et al. 2007; Deans et al. 2015). The recent growing interest in ontologies
633 has contributed to the establishment of multiple collaborative projects targeting different
634 biological entities (e.g., genes: The Gene Ontology Consortium 2000; cells: Bard et al. 2005;
635 gross anatomy: Mungall et al. 2012), model organisms (e.g., mouse: Hayamizu et al. 2005;
636 zebrafish: Sprague et al. 2008), and taxonomic groups (e.g., mammals: Smith et al. 2005).
637 Multispecies anatomy ontologies have been introduced for many taxa (e.g., amphibians:
638 Maglia et al. 2007; fishes: Dahdul et al. 2010b; spiders: Ramírez and Michalik 2014;
639 hymenopteran insects: Yoder et al. 2010) prompting assimilation of ontological knowledge in
640 studies of evolutionary phenotypes (e.g., Mabee et al. 2012), semantic-aware anatomical
641 descriptions (e.g., Mikó and Deans 2009; Silva and Feitosa 2019), and standardization of
642 morphological terminology (e.g., Vogt 2008, 2009; Vogt et al. 2010; Karlsson and Ronquist
643 2012; Porto et al. 2016, 2017). In other words, ontologies are the structured knowledge that
644 can be used to organize trait data in much the same way that phylogenies organize species
645 data.

646

647 *Does ontology carry phylogenetic information?* In this work, we have asked to what degree
648 phylogenetic information is structured by ontological knowledge by evaluating the BPI
649 content and phylogenetic dissonance among ontology-annotated anatomical data subsets. If
650 ontology carry any phylogenetic information, one would expect that sets of trees inferred
651 from data subsets annotated with related ontology concepts would also be more similar (e.g.,
652 Fig. 2: PCF and PVF). In other words, their posterior distributions would concentrate
653 probabilities in similar sets of trees. This would be indicated by high BPI and low
654 phylogenetic dissonance among data subsets representing semantically similar concepts.

655 When analyzing the BEE dataset, through the PROFILE analyses, we find that subsets
656 grouped based on anatomically related ontology concepts (i.e., ‘profiles’) actually exhibit

657 considerably high phylogenetic dissonance (Table 1, values between 8.5~14.7%). When
658 analyzing the FISH dataset, we find substantial information in many ontology-annotated data
659 subsets, but not universally across all anatomical subsets studied (Figs 4-5). Some clusters of
660 similar ontology terms represent groups of highly informative individual data subsets (Fig.4:
661 arrowheads) with high among-subset BPI (Fig. 4: blue circles) and moderate to low
662 phylogenetic dissonance (Fig. 4: red circles). These clusters include concepts referring to
663 some bones from jaws and branchial arches. These findings are consistent with the results
664 from the resampling analyses of the FISH dataset, which show that BPI for data subsets
665 containing characters annotated with the concepts of ‘maxilla’, ‘premaxilla’, ‘epibranchial’
666 and ‘ceratobranchial’ was higher than that of subsets based on a random resample of
667 characters (Fig. 6b). The analyses of both datasets show that ontology does indeed structure
668 phylogenetic information in some cases, thus prompting further investigation on the
669 underlying biological processes that may explain that. However, ontology concepts and their
670 relations do not fully explain phylogenetic information for all datasets and across all
671 anatomical entities—as might be expected given the somewhat limited set of relations present
672 in current anatomy ontologies. Instead, we observe that the semantic similarity dendrogram
673 relating ontology concepts (Supplementary Material: Fig. S3) and the dissonance dendrogram
674 relating posteriors inferred from the anatomical data subsets (Supplementary Material: Fig.
675 S4) have very different topology. This indicates that additional processes or other biases are
676 likely to also play a role in explaining BPI and dissonance values across anatomical subsets.
677

678 *How is phylogenetic information structured?* While we show that the ontology hierarchy does
679 carry signal in the structuring of phylogenetic information for some datasets and anatomical
680 concepts, it predictably does not do in all cases. Nevertheless, we can use the ontology
681 hierarchy to interrogate morphological data with ontology knowledge in search for

682 meaningful biological insights. Here, we asked if particular classes of anatomical entities
683 were more phylogenetically informative than others.

684 As for the BEE dataset, for example, most information was inferred from anatomical
685 entities instantiating concepts from mouthparts (e.g., ‘sitophore’, ‘labrum’, ‘stipes’),
686 prothorax (e.g., ‘profurcasternum’, ‘probasisternum’, ‘propleuron’), and metasoma (e.g.,
687 ‘male genitalia’, ‘female genitalia’). As for the FISH dataset, two main clusters of anatomical
688 entities (Fig. 5, heatmap, dashed boxes) provide most of the information for nodes recovered
689 in the phylogenetic species tree (Fig. 5: bottom tree). One cluster includes many concepts
690 from the jaw bones (e.g., ‘premaxilla’, ‘maxilla’, ‘dentary’); the other, many from the
691 branchial arch bones (e.g., ‘pharyngobranchial’, ‘epibranchial’, ‘ceratobranchial series’); and
692 most of these are developmentally associated with the dermatocranum (Supplementary
693 Material: Fig. S7: orange shades). The two clusters of concepts and their association with
694 ‘dermatocranum’ reinforce the findings that, for the FISH dataset, ontology seems to
695 structure phylogenetic information. The analyses of both datasets show that indeed
696 phylogenetic information is not uniformly distributed across anatomy ontology concepts.
697 Furthermore, anatomy entities do not provide the same information for all nodes in the
698 phylogenetic species tree. For the FISH dataset (Fig. 5, bottom tree, N1-N8), for example,
699 most information is inferred for N2-4 and N6, whereas N5 and N7 are inferred with little or
700 no information from individual anatomy ontology concepts. This indicates that despite
701 phylogenetic information not being uniform across all anatomical entities, it is still important
702 to include a ‘semantic diversity’ of anatomical concepts in order to provide resolution for as
703 many nodes as possible in the phylogenetic species tree.

704

705 *What sorts of processes may structure information?* If ontology hierarchy does not fully
706 explain the phylogenetic information inferred from data, which other processes may explain

707 it? Here we explored ontological knowledge summarized as a clustering dendrogram relating
708 anatomical concepts by semantic similarity. This dendrogram was used as a proxy to describe
709 anatomical/structural relations among real anatomical entities. These anatomical/structural
710 relations might be interpreted as the product of developmental processes affecting
711 morphogenesis of anatomical entities. Therefore, when we first asked the question whether
712 ontology structures phylogenetic information, we were interested in knowing if
713 anatomical/structural (~developmental) relations among traits can influence their evolution. In
714 other words, investigate if the evolution of some characters is non-independent due to
715 anatomical/structural associations and/or other biological processes.

716 Non-independence among characters can result in more similar posterior distributions
717 of trees inferred from dependent anatomical subsets—e.g., due to anatomical/structural
718 associations. It may also result from common functional/ecological factors shared across
719 species. Likewise, similar posterior distributions can simply be the result of shared
720 evolutionary history. Some anatomical subsets may produce posterior distributions that are
721 more congruent with the true species phylogeny (e.g., Fig. 1a,c). Others may agree within-
722 subsets and/or among-subsets but disagree with the true species phylogeny (e.g., Fig. 1b,d).
723 These can be easily accessed, for example, by contrasting posterior distributions for the
724 species phylogeny— inferred from other sources of data (e.g., molecular data)—with
725 posteriors inferred from data subsets annotated to each anatomical concept. Those agreeing
726 with the species tree posterior distribution (i.e., high BPI and low dissonance) would indicate
727 anatomical entities that evolved following the species phylogeny. Those disagreeing with the
728 species phylogeny but agreeing among themselves (i.e., low BPI and high dissonance in
729 relation to the assumed species tree posterior, but high BPI and low dissonance among
730 themselves) would indicate anatomical entities that evolved under processes other than
731 phylogeny, for example, concerted convergence due to shared functional/ecological factors

732 across unrelated species (e.g., Fig. 1a-b, squares and circles). Then, for those subsets agreeing
733 with the species phylogeny, it is possible to assess how much the phylogenetic information is
734 structured by ontology by contrasting clustering dendrograms based on semantic similarity
735 and phylogenetic dissonance (as discussed in previous sections). Finally, some anatomical
736 concepts may be inferred with low information due to few characters in the respective data
737 subsets and/or noise.

738 As it was shown before, the anatomical/structural ontology does indeed effectively
739 cluster some groups of anatomical concepts by their patterns of phylogenetic information, but
740 not for the entire anatomy. Conflict among anatomical subsets and the species phylogeny or
741 shared response to convergent selective pressures are likely candidates to explain the
742 evolution of these other traits. Indeed, results from the PROFILE analysis of the BEE dataset
743 demonstrates the former scenario (Table 1). Posterior distributions inferred from anatomical
744 entities associated with the same anatomy-based ‘profile’ (e.g., ‘mouthparts’, ‘head’, ‘legs’,
745 ‘wings’ etc.) have high levels of dissonance with each other, indicating that BPI in this case is
746 not structured by anatomical relations and there is considerable conflict among anatomical
747 subsets. As for the FISH dataset, the two clusters of concepts (Fig. 5, dashed boxes) indicate
748 that phylogenetic information is partly structured by ontology, as shown before, but also by
749 the species history, since most anatomical subsets in such clusters are inferred with
750 information supporting many nodes in the assumed species phylogeny (Fig. 5, bottom tree).
751 The MINI dataset shows an interesting case where the assumed species tree intentionally does
752 not correspond to the most probable species phylogeny. By enforcing a clade grouping all
753 miniatures (Supplementary Material: Fig. S8, N5), it was possible to observe different
754 processes likely structuring the phylogenetic information of anatomical subsets. For example,
755 a small cluster of related anatomical concepts referring to tooth rows from jaw bones of fishes
756 (Supplementary Material: Fig. S8, dashed box) indicate some structuring of phylogenetic

757 information by ontology, but not necessarily agreeing with a ‘true’ species phylogeny. On the
758 other hand, several unrelated anatomical concepts provide phylogenetic information for
759 Characidae (Supplementary Material: Fig. S8, species tree, bottom, N2), thus indicating
760 congruence with the ‘true’ species phylogeny, but no *semantic signal* (i.e., ontology does not
761 seem to structure phylogenetic information). Finally, characters from the anatomical concept
762 ‘premaxillary tooth row’ support the miniature clade, thus indicating a possible case of
763 concerted convergence due to miniaturization in such fishes.

764

765 *Alternative and complementary approaches.* We acknowledge that some questions addressed
766 here can be partially explored using existing or alternative methods. For example, there are
767 different methods for assessing support to bipartitions (splits), compatibility and/or conflict
768 among characters (Bandelt and Dress 1992: split decomposition; Hendy and Penny 1993:
769 spectral analysis; Chen et al. 2005: spectral partitioning). These methods are not at odds with
770 ours; they are complementary. Indeed we think they could also be enhanced by the inclusion
771 of the ontology-guided approach. Furthermore, our analyzes are based on entropy-derived
772 metrics of information and evaluate posterior distributions of tree topologies inferred from
773 groups of characters (i.e., subsets), instead of character-by-character. This enables evaluation
774 of how Bayesian (phylogenetic) information and conflict is structured by ontology and to
775 make meaningful comparisons among data subsets.

776 Another important distinctive aspect of our approach is that it adopts the definition of
777 “phylogenetic information” in the same sense as suggested in Lewis et al. (2016). Therefore,
778 our approach assesses the (Bayesian) phylogenetic information of data subsets. This is useful
779 because first, it considers not individual trees, but entire posterior samples, thus incorporate
780 phylogenetic uncertainty; and second, it allows comparisons of how the information in
781 different data subsets concentrate the probabilities from the prior set of possible tree

782 topologies into a different (or similar) set of trees in the posterior. By guiding these
783 comparisons with ontology knowledge and semantic distances, we can evaluate how
784 independent *conceptual* modules support or disagree with each other and with the overall
785 species tree topology—helping to alleviate a major challenge to morphological phylogenetics,
786 the non-independence of characters.

787

788 *Limitations and caveats.* One limitation of our approach is that it currently lacks a means to
789 formally test for statistical significance of differences in BPI and dissonance values.
790 Nonetheless, our intent was to help researchers assess the absolute and relative
791 information/dissonance among ontology-annotated anatomical data subsets, and using
792 ontologies to guide this exploration can help researchers to identify patterns across data
793 subsets that might be explained by particular ontological relations and/or biological processes.

794 In our study, we used the Phenoscape Knowledgebase (KB: <https://phenoscape.org>) to
795 calculate semantic similarity across all types of ontological relations present in the KB. We
796 noted that semantic similarity values calculated did not always correspond to our *a priori*
797 expectations in illuminating ways. For example, some characters annotated with different
798 ontology terms may share high semantic similarity because they share *is_a* relationships with
799 a particular ontology concept, such as characters annotated with terms that are subtypes of
800 (i.e., *subclasses_of*) the concept ‘calcareous tooth’, despite being *part_of* anatomical
801 structures in distinct body regions of a fish (e.g., ‘premaxillary tooth’, ‘maxillary tooth’,
802 ‘dentary tooth’). This suggests that disentangling the different types of relations between
803 terms (e.g., Vogt 2018a: *subsumption* vs. *parthood* relations) would allow for testing
804 alternative hypotheses for the ontology structure and relations that best reflect the
805 phylogenetic information inferred from anatomical data subsets. This would enable other
806 types of hypotheses to be tested using phylogenetic character matrices.

807 Doing so would alleviate one potential critique of using semantic similarity
808 dendograms—the expectation that ontological relationships will fully describe the actual
809 relationships among real anatomical entities instantiated by such terms. In fact, this should not
810 be expected given that ontologies do not contain complete information, and because unlike
811 phylogeny, there is no single bifurcating structure that can adequately describe all character
812 relations. Furthermore, anatomical concepts available in an ontology can vary depending on
813 the referential adopted (i.e., classification), terms can be characterized with varying degree of
814 detail (i.e., granularity), and organismal anatomies can be represented in multiple alternative
815 ways by different experts (i.e., semantic heterogeneity) (Vogt 2018b). Ontologies always
816 reflects design decisions among its creators and maintainers and, therefore, there is no single
817 correct scope or structure. For example, semantic similarity dendograms, depending on the
818 type of relations included in the reference anatomy ontology, may cluster terms such as ‘distal
819 process of premaxilla’, ‘distal process of maxilla’, and ‘distal process of dentary’ because
820 they all share the same *is_a* relationship (i.e., are different subtypes of) ‘distal process’ (i.e.,
821 *subsumption* relations), even though they are *part_of* different fish jaw bones (i.e., *parthood*
822 relations). Nonetheless, potential biases due to ontology choice or character annotation with
823 ontology terms can be directly assessed by comparing alternative ontologies in much the same
824 way that alternative phylogenies (or phylogenetic networks) can be compared to assess how
825 among-species variation is structured.

826 Another possible objection concerns the assumption that anatomical relationships
827 always conform to hierarchies and, therefore, can be represented as dendograms. Differently
828 from species phylogenies, where the process of descent with modification produces a clear
829 hierarchical pattern across species (for most organisms), for anatomical entities, such pattern
830 may or may not be expected as a general rule for anatomical relationships. However, some
831 studies do suggest this may be the case for some anatomical entities. For example, studies on

832 the evolution of cell types and eyes in Metazoa show that relationships among some
833 anatomical entities may in fact be well-represented as tree-like diagrams, both in
834 developmental and evolutionary time (Oakley 2003; Arendt 2008; Arendt et al. 2016).
835 Nevertheless, much like genetic data with frequent horizontal gene transfer, *semantic signal*
836 will often likely require multiple topological structures to best explain and predict character
837 similarity. We argue that interrogating datasets with these alternative sets of relations and
838 topologies is likely to reveal much about the processes governing morphological evolution,
839 and argue for the continued development of robust ontologies for organismal traits.

840

841 *Perspectives and future directions.* Applying ontology-guided approaches and moving beyond
842 the flat, one-dimensional partitioning of characters has enormous potential for making sense
843 of trait evolutionary patterns. For example, one can assess the phylogenetic information
844 provided by data subsets annotated to particular ontology terms in respect to one or more
845 nodes of interest in a given reference phylogenetic species tree (e.g., Fig. 5, bottom, species
846 tree). Node(s) in such trees may characterize clade(s) of organisms sharing a particular
847 biology or some traits of relevance; and by interrogating this node, we can discover and
848 identify subsets of morphological characters that are phylogenetically highly informative for
849 that particular node (e.g., Supplemental Material: Fig. S8: MINI dataset). Such an approach
850 can be expanded and generalized to any test statistic of interest that can be calculated across
851 the phylogeny or on a per character basis. For example, a researcher might be interested in the
852 magnitude of support for a rate shift at a particular node, rather than the BPI content at the
853 node given a particular reference ontology.

854 Such metrics can then be evaluated in light of the relationships among terms annotated
855 to character data subsets, including using different ontological relations (e.g., *part_of*,
856 *develops_from*) or distance metrics (e.g., *Jaccard*, *Resnik*) to build a semantic similarity

857 dendrogram. This can mirror the way that alternative phylogenetic tree topologies are used to
858 assess and compare phylogenetic information and signal across species, and they can shed
859 light on the underlying processes determining similar evolutionary patterns in morphological
860 traits. This approach can be employed, for example, to investigate if highly (or alternatively
861 slightly) informative data subsets annotated with particular anatomical terms share any
862 common underlying ontological relations. For example, we observed that most characters
863 informative for the FISH dataset are included in data subsets defined by ontology concepts
864 referring to bones that are *part_of* ‘dermatocranum’ (Supplemental Material: Fig. S7) thus
865 indicating possible structural/developmental dependencies among such traits.

866 Future research on Bayesian phylogenetic information will likely help to circumvent
867 the limitation to small datasets by using tree priors allowing for polytomies or better strategies
868 to sample posterior probability distributions (see discussions in Lewis et al. 2016). Further
869 studies could make use of alternative visualization graphs for the relationships among
870 ontology terms, using networks instead of dendograms, and the selection of specific types of
871 ontological relations, distance metrics, or subgraphs to represent the ontology structure (see
872 also Vogt 2018b for additional insights into using graphs in ontology-aware phylogenetic
873 analysis).

874

875 **SUPPLEMENTARY MATERIAL**

876 Data available from the Dryad Digital Repository: [http://dx.doi.org/XX.XX/XXX.\[XXXX\]](http://dx.doi.org/XX.XX/XXX.[XXXX]).

877

878 **FUNDING**

879 This work was supported by the National Science Foundation (NSF 1661516 to J.C.U., NSF
880 1661529 to W.M.D. and P.M.M., NSF 1661456 to H.L., NSF 1661356 to T.J.V. and J.P.B.).

881

882 **ACKNOWLEDGEMENTS**

883 We would like to thank the editors, Dr. Lars Vogt, and an anonymous reviewer for the
884 thoughtful revisions on this manuscript. We are thankful to members of Uyeda's lab for
885 valuable comments and suggestions on early drafts. DSP would like to specially thank
886 Matthew W. Pennell and his lab for the insightful discussions in their lab meeting. DSP is
887 grateful to Fabio A. Machado for helping fixing issues with the code used in *ontobayes*.

888

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